Business Applications as Economic Indicators

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Abstract

How are applications to start new businesses related to aggregate economic activity? This paper explores the properties of three monthly business application series from the U.S. Census Bureau's Business Formation Statistics as economic indicators: all business applications, business applications that are relatively likely to turn into new employer businesses ("likely employers"), and the residual series -- business applications that have a relatively low rate of becoming employers ("likely non-employers"). The analysis indicates that growth in applications for likely employers significantly leads total nonfarm employment growth and has a positive correlation with it, whereas growth in all applications and applications for likely non-employers have weaker positive correlations and shorter leads. Furthermore, growth in applications for likely employers leads growth in nearly all of the monthly Principal Federal Economic Indicators (PFEI) included in this study. Impulse response functions from vector autoregression analysis indicate that growth of both total nonfarm employment and advance monthly sales in retail and food services have positive and long-lasting responses to innovations in growth of applications for likely employers. Overall, applications for likely employers appear to be a strong leading indicator of monthly PFEIs and aggregate economic activity, whereas applications for likely non-employers provide early information about changes in increasingly prevalent self-employment activity in the U.S. economy.

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1. Introduction

Employer business startups (new firms with paid employees) have a critical role in job creation and productivity growth in the U.S. economy.[1] Most startups either fail or remain small, but some grow into large and productive firms, in the process transforming industries and the economy. The economic impact of startups is not only limited to the jobs created by them, but also include many positive externalities, pecuniary and non-pecuniary, on other aspects of the economy, such as new demand for suppliers and construction, and innovation spillovers.

Startup activity and the performance of young firms are particularly sensitive to business cycles and economic conditions. For example, there was a major drop in the number of business startups in the early phases of the Great Recession. However, this drop was only visible in hindsight due to a lack of high-frequency, timely, and up-to-date data on business formation in the economy based on data available at the time.

The availability of timely data on business formation can enhance our understanding of changes in entrepreneurial activity when aggregate economic conditions worsen or improve. Moreover, high-frequency movements in new business formations themselves have the potential to foretell changing economic conditions, as entrepreneurs may react to early signs of such changes and reassess their business plans. Recent research also indicates that early characteristics and initial conditions of businesses tend to be influential in post-entry business growth and dynamics.[2] Measuring the volume and nature of early-stage business activity is therefore critical in assessing the contribution of likely new businesses to the U.S. economy.

Until recently, comprehensive, timely, and high-frequency data on new business initiations has not been available. The Census Bureau's Business Formation Statistics (BFS), initially released in 2018 as a quarterly data product, fills this gap by providing monthly data on new business applications, and actual and projected employer business formations originating from these applications.[3] The monthly BFS is released within ten days of the end of the reference month. A core set of business application series are also released weekly on the Thursday following the end of the reference week.

The BFS has been particularly useful in real time tracking of new business activity during the COVID-19 Recession at weekly frequency, and at sectoral and state-level detail. Following a sharp drop in business applications during the early phases of the pandemic, there has been a substantial surge that resulted in an all-time high in business applications for the period starting in 2004. The weekly BFS data has been widely followed during the pandemic, as policymakers, government agencies, and business community monitored the weekly progression of business

[1] See, Haltiwanger, Jarmin, and Miranda (2013).
[2] See, e.g., Bayard et al. (2018), Brown et al. (2019), Guzman and Stern (2020), and Sterk, Sedlacek, and Pugsley (2021).
[3] See Bayard et al. (2018) on the construction of the BFS series.

applications to assess the impact of the pandemic on entrepreneurship. The strong surge in new business applications during the pandemic contrasts sharply with the substantial decline in activity amongst existing small businesses (see, e.g., Buffington et. al. (2021)). The state and sector-level disparity in the dynamics of business applications has also attracted considerable attention (see Haltiwanger (2021)). Most of the surge in business applications after the initial drop in early 2020 was attributable to the retail sector, and the largest increase within retail was observed in non-store retailers, which include mainly e-commerce businesses. On the geographic dimension, while the states in the Northeast and West were the hardest hit early on, states in the South and Midwest led the recovery in applications.

Earlier work on the properties of BFS series generally indicates that the dynamics of business applications is closely related to shifts in aggregate and local economic activity. Dinlersoz at al. (2021) show that aggregate business application and formation activity fell at the start of the Great Recession and the COVID-19 Recession, but the time-path of applications and formations have been quite different for the two recessions. Business applications and projected formations fell sharply as the pandemic worsened in the first quarter of 2020, but then they recovered quickly before reaching all-time highs by mid-2020. In contrast, during the Great Recession applications and actual formations fell and did not quite recover to their pre-recession levels for an extended period.[4]

The microdata underlying BFS also help track economic conditions at a more granular level of geography. Bayard et al. (2018) find that business applications have been higher in counties that experienced higher employment growth since the end of the Great Recession and lower in metro areas that experienced higher house price declines during the Great Recession. In addition, the number of applications rose more rapidly in counties where shale oil and gas extraction activity were more intense during the 2010s.

Despite the prior work that hints at a connection between business applications and aggregate and local economic activity, there has been no systematic work to establish more formally the properties of the BFS series as indicators of aggregate economic activity. In particular, an open question is whether the BFS series contain early information on changing aggregate economic conditions and how strong this information is compared to that provided by various existing Principal Federal Economic Indicators (PFEIs). The objective of this paper is to examine the behavior of certain monthly business applications series from the BFS in relation to 19 monthly PFEIs and assess their ability to capture the month-to-month growth in these indicators.

While the BFS series consists of four application and eight formation series, the analysis in this paper focuses on a parsimonious subset of application series. The two main application series studied are Business Applications (BA) and High-Propensity Business Applications (HBA). BA is the broadest set of business applications, including applications that may result in either new

[4] See Dinlersoz et al. (2021) for a comparison of the dynamics of business applications and formations during the two recessions.

employer or non-employer businesses. Data provided in the application offers information on the likely outcome of the application. Using this data, HBA is defined as the set of high propensity applications with certain characteristics that make them more likely to transition into an employer business. These characteristics include information that the new business plans to hire workers or will be incorporated or is in sectors where new businesses are more likely to be employers. As shown in Bayard et. al. (2018) and Haltiwanger (2021), HBA tracks actual employer startups over the next 4 to 8 quarters very well.

The analysis also separately considers the difference between BA and HBA, or Non-High-Propensity Business Applications (NHBA), which is referred to here as the set of likely non-employer applications. Haltiwanger (2021) shows that NHBA closely tracks fluctuations in non-employers at an annual frequency.[5] The increasing prevalence of self-employment and gig jobs in the U.S. economy makes this series a critical one for understanding the trends in self-employment.

As further discussed in Section 2, these three series contain the core of the information about business applications. We do not use the actual business formation series for the current analysis since these series are not timely. Similarly, we do not use the projected business formation series which while insightful are largely derived from the application series (specifically HBA) that are the focus of the current paper. Given our interest in understanding the timing of fluctuations in business applications with other timely high frequency key economic indicators, we focus on the core application series that provide guidance about the forward-looking plans of potential future new businesses.

The analysis first examines, using cross-correlations and correlograms, pairwise correlations between growth in monthly application series and the growth in various monthly PFEIs for several lags and leads. We focus on the relationship between business applications with nonfarm employment as the latter is a critical coincident indicator of economic activity. The correlograms indicate that growth in BA, HBA, and NHBA all lead growth in nonfarm employment, but HBA has the highest correlation and the largest lead. Furthermore, HBA strongly leads most of the monthly PFEIs considered. In terms of the strength of correlations with nonfarm employment, HBA is around the middle of the PFEIs studied, but BA and NHBA rank at the bottom. HBA's lead of nonfarm employment is quite large (11 months), and it surpasses all PFEIs on this front except for New Single-Family Homes Sold. BA and NHBA, on the other hand, are more mildly leading (5 and 1 months, respectively). Overall, HBA has the highest correlation, in absolute terms, with nonfarm employment among all other PFEIs, and the lowest correlation with Real Hourly Earnings Production and Nonsupervisory Employees. The sectoral components of HBA

[5] Research in progress by Dinlersoz and Luque (2021) focuses on estimating the rate of non-employer business formation from business applications from the micro data. This work will help refine our understanding of the relationship between business applications and new non-employers much like the Bayard et. al. (2018) research provides guidance about the relationship between business applications and employer startups.

also appear to lead the sector specific PFEIs. For instance, manufacturing HBA leads the manufacturing related PFEIs. Similarly, retail HBA leads the retail related PFEIs.

To provide perspective, we contrast the relationship between HBA and other PFEIs with Advance Monthly Sales Retail and Food Services (or retail sales for short). Retail sales is a strong leading indicator for most other PFEIs but with a shorter lead time compared to HBA. For example, retail sales lead nonfarm employment by 4 months while the lead for HBA is 11 months. On the other hand, retail sales have much stronger correlations with other PFEIs than HBA.

We also use vector autoregressions to shed further light about the timing and magnitude of the relationships between business formations and other PFEIs. Again, we compare and contrast the impulse response functions to an innovation in HBA vs. an innovation in retail sales. We find that a positive innovation to HBA growth induces a positive, statistically significant hump shaped response in nonfarm employment growth that lasts nearly 25 months. On the other hand, an innovation to nonfarm employment shock does not have a significant impact on HBA, indicating no apparent reverse relationship. An innovation in retail sales growth also induces a positive hump shaped response in nonfarm employment growth. The peak effect is earlier and somewhat stronger. The reverse relationship is present, but weak. Shocks to HBA and retail sales both account for a significant fraction of the *n*-step ahead forecast error of fluctuations in nonfarm employment growth rates.

Overall, the analysis suggests that HBA is a novel leading indicator for many PFEIs that receive much attention in economic measurement. The fact that HBA has a substantial lead over many of prominent PFEIs examined here suggests it provides a very early signal of changing economic conditions. While BA and NHBA are relatively less informative indicators of overall economic activity, they are of particular interest as they contain unique information on an increasingly important component of economic activity less well-captured by the existing PFEIs: self-employment. Further work is needed to establish more properties of the BFS series analyzed in this paper; in particular, the properties of NHBA series.[6]

The idea of using information on new business formation as an economic indicator is not entirely new. An earlier monthly series on new business activity was released by the Bureau of Economic Analysis (BEA) starting in 1947 until the mid-1970's. This series was based on the number of new business incorporations by Dun and Bradstreet and other confidential information reported to the BEA. However, the coverage was limited to various states and new corporate entities, and also included expansions of existing corporations.[7] This series was designated as a leading

[6] Dinlersoz and Luque (2021) aim to provide evidence on the properties of NHBA series and non-employer business formations from the applications included in NHBA.

[7] Specifically, the statistics included new business that incorporated, existing businesses changed from the noncorporate form to the corporate form, existing corporations given authority to operate in another state, and existing corporations transferred to a new state. See Business Conditions Digest, November-June (1968-1969).

economic indicator by National Bureau of Economic Research (NBER), but there appears to be no detailed information on how this indicator status was established. Compared to this earlier series, the BFS series has a number of advantages. It is based on federal administrative data, it covers all legal forms of organizations, not just corporations, it includes all states and the District of Columbia, and it allows for sectoral analysis.

The rest of the paper proceeds as follows. Section 2 describes the BFS series and discusses the reasoning behind the selection of the business application series we focus on. Section 3 provides a background on PFEIs. The technical analysis in Section 4 establishes some key properties of the business application series with respect to the existing PFEIs based on correlation and vector autoregression analysis. Section 5 concludes.

2. Business Formation Statistics

This section gives some background on the BFS and describes the series included in it. It then motivates our focus on three specific series from the BFS, which we study in more detail in relation to the PFEIs.

2.1. The origins and definitions of BFS series

The Business Formation Statistics (BFS) is currently a Census Bureau experimental data product which offers timely, high-frequency, and comprehensive information on new business applications, as well as actual and projected employer business startups in the United States. The BFS started as a research project at the Center for Economic Studies in collaboration with economists at the Federal Reserve Board, Federal Reserve Bank of Atlanta, and the universities of Maryland and Notre Dame. Research behind the construction of BFS data series is documented in detail in Bayard et al. (2018).

The BFS relies on applications for Employer Identification Numbers (EINs) made to the Internal Revenue Service (IRS) using IRS Form SS-4 and delivered on a weekly basis to the Census Bureau.[8] EIN applications data are matched with Census Bureau's Longitudinal Business Database (LBD), which provides information on the incidence and timing of new employer business formation. This match identifies whether an EIN application becomes an employer business following application and if so, the year and quarter of first payroll on record in LBD. The combined data are used to construct nationwide, industry, and state level time series for business applications and business formations originating from these applications.

[8] The detailed contents of the IRS Form SS-4 are available at https://www.irs.gov/pub/irs-pdf/fss4.pdf.

There are four business application series and eight business formation series in the BFS. The core series is Business Applications (BA), which contains all EIN applications excluding those made without a business intent, such as trusts, estates, public entities, and others related to personal finance and household tasks. Among BA, there is a high degree of heterogeneity in terms of the likelihood of becoming an employer business in the future. Certain broad application characteristics revealed in IRS Form SS-4 during the EIN application process are highly correlated with employer business formation. Using these characteristics, applications are further classified into a subset of BA that represents "likely employers" – labelled as High-Propensity Business Applications (HBA). HBA satisfy one or more of the following criteria: (i) from corporations, (ii) indicate hiring an employee, purchasing an ongoing business, or changing organizational form, (iii) indicate a first wages paid/planned date, and (iv) in certain industries: manufacturing, food and accommodation services, health care, and part of retail. Overall, HBA have about 27% likelihood of becoming employer businesses within 8-quarters after application, as opposed to the non-HBA (NHBA), which become employer businesses with a probability of only 3.8%.[9]

Two subsets of HBA exhibit particularly high rates of employer business formation. One is the set of applications that indicate a first wages paid/planned date, which have nearly 40% likelihood of transitioning into an employer business within 8-quarters of application. The other is the applications from corporate entities, which turn into employer businesses at a rate of approximately 30%. These two subsets are tracked over time as separate series in the BFS in addition to HBA: Business Applications with Planned Wages (WBA), and Business Applications from Corporations (CBA). Altogether, HBA, WBA, and CBA are informative about "likely employer" business formations, whereas NHBA series indicates "likely non-employer" business activity.[10]

In addition to the business application series described above, the BFS contains eight business formation series. Business Formations within 4 Quarters (BF4Q) provides the count of actual employer businesses that originate from business applications within four quarters of the time of application. Because the LBD used in identifying business formations has a typical lag of 2 years, actual formations for recent applications are not observed in a timely fashion. To fill this gap, the BFS uses an econometric model to estimate business formations from a given set of

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[9] See Bayard et al. for the rates of employer business formation associated with different application characteristics (2018).

[10] Appropriate caution is needed in interpreting the term "likely". Less than half of the HBA applications yield an employer startup but as discussed below fluctuations in HBA track fluctuations in employer startups very closely. For likely non-employers, we know less about the time series patterns of new non-employers, but the analysis below shows projected non-employers using a constant exit rate from Davis et. al. (2009) and NHBA as a proxy for entrants tracks actual non-employers closely.

applications and provides projections of business formations for recent periods based on this model.[11] Projected Business Formations within 4 Quarters (PBF4Q) is the resulting series.

Combining BF4Q and PBF4Q, an up-to-date series that includes both formations and projections for recent periods is also provided – Spliced Business Formations within 4 Quarters (SBF4Q). In addition, the BFS provides information on the duration between business applications and formation, conditional on an actual formation. The duration series is called Average Duration (in Quarters) from Business Application to Formation within 4 Quarters (DUR4Q). The BFS also contains another set of business formation series, which are defined analogously to the 4-quarter window series, but use an 8-quarter window to measure business formations from applications (these series are formally labelled in the BFS as BF8Q, PBF8Q, SBF8Q, and DUR8Q, respectively). The BFS application and formation series together offer a rich picture of early stage business formation activity in the U.S. economy.

The BFS was originally released with quarterly data for public use in 2018. The release of BFS continued at a quarterly frequency between 2018 and 2020, with the earliest data pertaining to 2004q3. The quarterly BFS aggregated applications to a quarterly frequency, even though applications are transmitted to Census Bureau from IRS at a weekly frequency. Up until 2020, the BFS time series included data on only one recession: The Great Recession that officially started in 2007q4 and ended in 2009q2. As economic conditions rapidly deteriorated with the onset of the pandemic in the first quarter of 2020, the demand by policymakers for near real-time data sources for measuring economic activity surged. This demand presented a unique opportunity for BFS to monitor business formation activity at a higher frequency. Recognizing its potential as an early indicator of fast-evolving economic conditions during the COVID-19 recession, the Census Bureau started releasing the BFS at a weekly frequency on April 8, 2020 for a limited number of series (BA, HBA, WBA and CBA).

Weekly frequency is the highest frequency with which the underlying administrative data for the BFS is received by the Census Bureau. In many ways, the BFS program was already prepared to handle such high frequency, as the basic building blocks of the quarterly BFS were weekly batches of applications received on a timely fashion. Importantly, the BFS has also initiated a monthly release starting in January 2021 with the complete set of business application and formation series. The monthly BFS builds on the same infrastructure as weekly. It replaces the quarterly BFS and includes additional critical components including all of the series at the 2-digit NAICS level. The new monthly frequency is crucial for the purpose of comparing BFS series with other economic indicators, as most of the principal federal economic indicators are monthly -- a few others are quarterly, one is semi-annual, and only one is weekly, as discussed in Section 3.

[11] See Bayard et al. (2018) for the details of the econometric model. In a nutshell, a linear probability model is used to relate the indicator of business formation from an application to application characteristics.

In principle, the weekly BFS series could also be considered for the type of analysis in this paper. However, there are at least two impediments in assessing the properties of the weekly series. First, the Census Bureau has not yet developed a seasonal adjustment algorithm that can readily be applied to various weekly series. The weekly series are very noisy compared to the monthly, and the unadjusted series exhibit movements that are not related to overall economic conditions. For instance, weekly applications drop around major holidays, and there is a steady build-up in the weeks leading up to the federal tax deadline. Second, as mentioned above, most other PFEIs are monthly and only one is weekly. Therefore, using a weekly frequency series would substantially limit the number of PFEIs and other established economic series available for comparison. In the future, properties of the weekly series can be studied when seasonal adjustment becomes available. One major advantage of the weekly series is that they can be potentially more informative about the turning points in the economy compared to the monthly series.

2.2. The focus on BA and HBA as economic indicators

While all 12 series in BFS provide critical information on different aspects of business applications and formations, we argue that a parsimonious subset consisting of the BA and HBA series, and the series for their difference, Non-High-propensity Business Applications, can serve as indicators of the different aspects of aggregate economic activity. Note that NHBA is not a series separately released as part of the monthly BFS, but rather an implicit series derived from BA and HBA. As such, for the purposes of this study NHBA series is not separately seasonally adjusted (direct adjustment) but is obtained as the difference between the seasonally adjusted BA and HBA series (indirect adjustment). However, NHBA obtained this way may have residual seasonality. An alternative is to seasonally adjust separately the two components of BA: HBA and NHBA. In the future, if a decision is made to release NHBA as a standalone series in BFS, this alternative may be pursued. There is, however, no consensus in the literature as to whether direct or indirect adjustment is superior.[12] Future work may study the differences between the two approaches in the context of NHBA.

BA, HBA, and NHBA broadly capture key dimensions of early stage business formation. First, for the task of tracking overall business initiation activity in the economy, BA is the most comprehensive series, as it contains information on both "likely employer" and "likely non-employer" applications. This broad coverage makes it appealing as a potential indicator of both future new job creation and new self-employment, especially as the gig-economy continues to grow, and new employer business formation rate continues to decline.

Second, HBA is particularly useful in understanding the behavior of applications that can turn into job creators in the near future with a relatively high likelihood. While the two subsets of

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[12] See, e.g., Hood and Findley (2003) and Evans (2009).

HBA (WBA and CBA) have higher likelihoods of transitioning into employer status than HBA, they also leave out a large chunk of applications that still have a considerable probability of turning into job creators. HBA make up nearly 50% of applications, whereas WBA and CBA each constitute about 24% of the applications with a large overlap between the two.[13] Thus, HBA is a more comprehensive measure of potential new employer businesses that can form in the future. Furthermore, HBA tend to follow the trends in actual and predicted business formation series (SBF4Q, SBF8Q) relatively closely. Figure 1 presents the series BA, HBA, WBA, CBA, SBF4Q, and SBF8Q. The correlation in HBA and SBF8Q is 0.88 while the correlation between BA and SBF8Q is only 0.32. The latter low correlation is consistent with BA including a large portion of likely non-employer applications (nearly 50% of BA consists of likely non-employer applications). The high correlation between HBA and SBF8Q reflects the close correspondence between HBA and employer startups. Since projected startups are based on the relationship between application characteristics and actual startups, it is instructive to focus on the correlation between HBA and SBF8Q through 2016 so that only actual startups are used. The correlation between HBA and actual startups for the 2004 through 2016 period is 0.89.

Third, the difference between BA and HBA, NHBA, is relevant in terms of tracking non-employer business activity. Drawing from Haltiwanger (2021), Figure 2 shows a close correspondence between the actual non-employer series and that projected from a simple transition equation using NHBA as a proxy for non-employer entrants.[14]

The rise in likely non-employer business applications can be a particularly important indicator of worsening economic conditions and recessions, during which some displaced workers are pushed into self-employment. In fact, the surge in NHBA during the COVID-19 Recession may be partly due to this dynamic.[15] In addition, a rising trend in NHBA is consistent with the change in the employment patterns, consistent with the increasing prevalence of gig economy jobs. Note that NHBA cannot account for all new non-employer business activity, as most of such activity can be conducted using a Social Security Number as a tax ID rather than an EIN. Even then, non-employers with an EIN tend to have a larger scale (in terms of revenue) compared to those without an EIN, so NHBA could be informative about likely non-employer businesses that tend to perform better than the average non-employer.[16]

Finally, application series have critical advantages over business formation series as timely indicators. The actual formation series BF4Q and BF8Q have a lag of two years, so they are not timely. While the projected formation series PBF4Q and PBF8Q fill the gap in the actual

[13] See Bayard et al. (2018).

[14] The transition equation is: $NES_t = (1 - ExitRate_t) * NES_{t-1} + NHBA_t$. The exit rate is estimated from Davis et. al. (2009). See Haltiwanger (2021) for more details. Appropriate caution is needed in using this measurement approach since NES includes sole proprietor, non-employers not captured in NHBA. The index number approach in Figure 2 alleviates implied level differences but the lack of information on entry of sole proprietor, non-employers still suggests caution.

[15] See Dinlersoz et al. (2021).

[16] See Davis et al. (2009)

formation series, they are model-based estimates. The model uses various application characteristics to estimate the likelihood of employer business formation from an application. The most critical of the characteristics used in the model are the ones that underlie the definition of HBA. As such, while the model uses additional information that is not contained in the definition of HBA, most of the key information is already captured by HBA – this is evident in Figure 1, where HBA tracks the trends in SBF4Q and SBF8Q relatively closely.[17] The remaining two series, DUR4Q and DUR8Q, are informative about the delay in employer business formation, which has been trending up over the BFS sample period. Changes in the delay in hiring can be tied to the underlying economic conditions; for instance, increasing uncertainty. However, just like the actual business formation series they are based on, the duration series have a lag of two years, and they also do not provide information on the volume of business formation activity.

Figure 3 contains the three BFS series the rest of the analysis focuses on. The HBA and NHBA series display very different patterns. The former declines substantially as the Great Recession hits and stays relatively flat until the COVID-19 Recession. In contrast, after a slight decline NHBA grows persistently between the Great Recession and the COVID-19 Recession, before dropping sharply and subsequently reaching all-time highs. As a result, the gap between the NHBA and HBA series opens up over time. The time-path of the BA series, on the other hand, is influenced mainly by the trends in the NHBA series. As noted above, HBA tracks actual employer startups closely while NHBA exhibits a negative correlation with actual employer startups (-0.58).

For the reasons outlined above, the rest of the analysis focuses on the properties of the monthly BA, HBA, and NHBA series as economic indicators. An attractive feature of these series is their economic relevance, high frequency, timeliness, and not being subject to significant revisions and availability of long time series.[18] The rest of the analysis compares these three series with existing monthly Principal Federal Economic Indicators (PFEIs) and seeks to understand whether any of these series lead, coincide, or lag the PFEIs.

[17] In addition, the model parameters are estimated using actual formations from at least two years prior to the current year, and there may be shifts in the model parameters as economic conditions change in recent periods for which actuals are not yet available. While the model-based projections have done quite well in normal economic times (i.e. 2010-2019), their behavior during recessionary periods is less understood and tested. For instance, information on actual business formations during the pandemic in 2020 will not be available until 2022. The extraordinary change in business application activity and in the composition of applications in 2020 could presumably result in a business formation pattern quite different than the projections based on the model estimated using data from the 2016-2018 period.

[18] These criteria are stated in the 2019 guidelines on producing leading, composite and sentiment indicators by United Nations Economic Commission for Europe (UNECE).

3. Principal Federal Economic Indicators (PFEIs)

Policy directives issued by the Office of Management and Budget (OMB) provide guidelines for the production and release of a Principal Federal Economic Indicator (PFEI). As defined by Statistical Policy 3, PFEIs are those "statistical series that are widely watched and heavily relied upon by government and the private sector as indicators of the current condition and direction of the economy" (U.S. Office of Management and Budget, 1985).[19] Statistical Policy 3 also controls the release of and methodological updates to these PFEIs. OMB has granted PFEI status to 36 statistical data products that are published by 8 different federal statistical agencies, including the Census Bureau, the Bureau of Labor Statistics, the Federal Reserve, and the Bureau of Economic Analysis. Table 1 provides a summary of all existing PFEIs. The Census Bureau currently publishes 13 PFEIs, more than any other agency. The last new PFEI to be designated by the OMB was the Energy Information Administration's Weekly Natural Gas Storage Report in 2007.

As Table 1 shows, PFEIs are published at a variety of frequencies: weekly, monthly, quarterly, and semi-annual. The BFS is a monthly data product; therefore, for our analysis we focus on the monthly PFEIs and further subset to those PFEIs with characteristics that would be particularly useful in the analysis of potential BFS indicator properties. This subset of indicators used in the analysis are denoted with an asterisk (*) in Table 1 and represent measurements that capture economic activity in personal and business consumption, construction, manufacturing, and employment. The data series from each of the PFEIs used in the BFS analysis are summarized in Table 2.

Some of the monthly PFEIs in Table 1 are not considered in the analysis for a variety of reasons. As a general point, we focus on monthly indicators that track nonfarm private sector business activity where new business applications are potentially more relevant. In general, the PFEIs focused on international trade, agriculture, prices, and natural resources have less of a relevance to the BFS series. International trade is dominated by large, established firms, and only a tiny fraction of new employer businesses are engaged in international trade.[20] Agriculture is a relatively small part of the economy, and business applications in agriculture sector is a very small fraction of total applications.[21] The fluctuations in natural gas storage is less related to new firm formation and more to the inventories held by existing natural gas producers. The natural gas market reacts to changes in inventory levels, which informs trading decisions that move natural gas prices. Price indices (Consumer Price Index and Producer Price Index) are driven by many of the same economic conditions impacting overall business activity but have complicated

[19] U.S. Office of Management and Budget (1985). Statistical Policy Directive No. 3: Compilation, release, and evaluation of principal federal statistical indicators. 50 Federal Register 38932 (September 25, 1985). Available: Federal Register Notice (archives.gov)

[20] See, e.g., Bernard, Jensen, Schott (2009) and Bernard, Jensen, Redding, Schott (2018) for evidence that U.S. traders tend to be very large and trade volume is highly concentrated among the top traders.

[21] See sector level business applications data: Special Projects - Weekly BFS by Industry (https://www.census.gov/econ/bfs/projects.html).

dynamics given the adjustment process of prices. Such adjustment dynamics are interesting in their own right but not the focus of this study. There may be a connection between firm entry and markups, but price indices do not provide direct indicators of markups.[22]

There is relatively little formal documentation of the processes or research behind the determination of whether a statistical data product is or is not PFEI. Furthermore, there is limited research on understanding the nature of PFEIs in terms of whether they lead, lag, or coincide with, economic activity. Our analysis below documents some properties of the monthly PFEIs alongside with the properties of the BFS series we consider. However, this analysis is not meant to be a comprehensive look at unique properties of each PFEI, an endeavor beyond the scope of this article.

In addition to the PFEIs, there are many other economic indicators and indices derived from the PFEIs or their components, and additional data, such as stock prices and interest rate spread. These are regularly released by private entities, non-profit institutions, and other government agencies. For instance, the Federal Reserve Banks and the Conference Board maintain a set of economic indicators/indices that are released on a regular basis. These other indicators and indices contain valuable additional information to assess the properties of the business application series studied here. In future work, we plan to include some of them in the analysis. It is worth noting that several of the monthly PFEIs that we analyze are included in the Conference Board's leading, coincident and lagging indicators.[23] The Conference Board's leading indicators includes subcategories of manufacturing new orders and building permits for new private residences and coincident indicators include nonfarm payroll employment, industrial production and manufacturing and trade sales.

4. Properties of business application series in Relation to PFEIs

To explore the relationship between business applications and the PFEIs we focus initially on the sample period from 2004:7 (the start of the monthly BFS) through 2019:12. We do this for two reasons. First, as is already evident from Figures 1 and 3, there are dramatic fluctuations in the business applications during the COVID-19 pandemic that are unprecedented in magnitude and also quite distinct from the patterns in the Great Recession. Second, new business applications are inherently forward looking since the analysis in Bayard et. al. (2018) shows that it takes up to two years for HBA applications to yield actual new employer business startups. Therefore, the surge in business applications in the second half of 2020 is unlikely to have its full effect on employer startups and in turn other indicators of economic activity until late 2021 and into 2022

[22] For recent work on the connection of markups and entry in a macroeconomic context, see, e.g., Cavallari (2013), and Lewis and Stevens (2015).
[23] See https://www.conference-board.org/pdf_free/press/US%20LEI%20-%20Tech%20Notes%20MARCH%202021.pdf

(that is well into the future). While it is clear that the BFS and other PFEIs exhibit unprecedented volatility in 2020 and 2021, we also include analysis to help draw out what makes this period different after our initial exploration of the 2004-2019 period.

4.1. Using cross-correlations to study properties of business application series

In this section, we aim to understand the relationship between the BFS series and the existing monthly PFEIs. In particular, we explore to what extent BFS series correlate with other PFEIs, and whether they lead, coincide, or lag the PFEIs in terms of monthly growth.

We start with the concrete example of the relationship between HBA and nonfarm employment. We ask the following questions:

1. Does HBA lead nonfarm employment? We say that HBA leads nonfarm employment if movements in its growth rate typically precede those of nonfarm employment. If movements in these two series tend to take place at the same time, then we say that they are coincident. If HBA moves after nonfarm employment does, then it lags nonfarm employment.
2. What are the direction and magnitude of the correlations between the growth rate of HBA and growth in nonfarm employment?

We calculate the cross-correlations between the monthly year-over-year growth rates of these two series. This cross-correlation analysis provides a simple way of addressing the questions posed above.

We first define the cross-correlation function between variables x and y, which in our case are monthly year-over-year growth rates of the economic series of interest, as

$$\rho_{xy}(k) = corr(x_t, y_{t+k}),$$

where k is an indicator of the lag time of y and $corr$ is a function that calculates the correlation between two variables. Thus, we calculate the correlation between the contemporaneous growth rate of nonfarm employment (x above) and the growth rate of HBA (y above) for lags and leads that range from -12 to 12 (k above).

The results of this exercise can be seen in the cross-correlogram in Figure 4a. The x-axis of the graph indicates the value of k used to calculate the correlation. Note that for $k < 0$, indicated by the values to the left of zero on the x-axis, the analysis uses growth rates of y from previous periods. If the correlations are highest in this region then y is a leading indicator. On the other hand, when $k > 0$ (the values to the right of zero), the analysis uses growth rates from future periods of y. If the correlations are highest in this region then it is a lagging indicator. For $k = 0$, the analysis uses contemporaneous values of y. Thus, if the correlations are highest when $k = 0$, then it is a coincident indicator. Backus, Routledge, and Zin (2010), and Stock and Watson

(1998) conduct the same type of cross-correlation analysis to determine the properties of macroeconomic series.

The figure shows that the growth rates of the two series are positively correlated for all values of k. Furthermore, the highest correlation is for $k = -11$. Thus, HBA leads nonfarm employment growth by 11 months and the correlation at that lead is 0.64. The interpretation is that the HBA growth rate from 11 months prior is the best predictor of the current growth rate in nonfarm employment. Thus, we conclude that growth in HBA is a useful indicator in predicting future changes in the growth in nonfarm employment.

For comparison, Figure 4b repeats the analysis with retail sales instead of HBA. Retail sales is a key PFEI, since many standard macroeconomic models would imply an early consumption response to changing economic outlook, since consumption generally reflects consumers' expectations about employment outlook and real wage growth.[24] Retail sales indeed leads nonfarm employment by 4 months, and the correlation at that lead is 0.85. While HBA has a lower correlation with non-farm employment compared to retail sales, it has a substantially larger lead.

4.2. Results of cross-correlation analysis

We apply the cross-correlation analysis described above to analyze the relationship between nonfarm employment and the BFS series along with other PFEI's. For all variables, we focus on the monthly year-over-year growth rates.

Table 3 shows a summary of the results of the cross-correlation analysis for the three BFS series (BA, HBA, and NHBA) and all of the PFEIs considered.[25] The table indicates whether the series is leading or lagging, the strength of the correlation, and the number of periods that it leads/lags by (timing). The table is sorted by the strength of the correlation from the strongest to weakest correlations.

Table 3 has a few key findings. First, almost all the PFEIs lead nonfarm employment. Furthermore, the PFEIs that lag nonfarm employment do so by only one or two months. This result suggests that the existing PFEIs are mainly economic indicators that are leading or coincident. Second, HBA leads nonfarm employment by 11 months, which is one of the highest lead times in the table. The correlation between growth in HBA and growth in nonfarm employment is 0.64, which is in the middle range of the PFEIs considered. Third, the growth rates of BA and NHBA are positively correlated with that of nonfarm employment although these correlations are among the weakest of the series analyzed. In terms of timing, BA is mildly leading by 5 months and NHBA leads by only one month.

[24] See, e.g., Breeden (2012).
[25] Table 3 does not include total private sector employees and the unemployment rate due to the high correlations with nonfarm employment.

Table 4 reports the results of a similar exercise in which we calculate the correlation of the growth rate of the other PFEI's and the growth rates of HBA. This table gives us information about whether HBA leads or lags the other PFEIs. First, we find that HBA leads almost all the other PFEI's. This result is consistent with Table 3 in which HBA leads nonfarm employment by 11 months, substantially more than almost all of the other series.

Table 3 shows that retail sales have the highest correlation with nonfarm employment among all the PFEIs that we consider. One important difference between HBA and retail sales is that the latter tends to lead nonfarm employment by less (4 months compared to 11 months for HBA). In order to put the results from Table 4 into perspective, in Table 5 we repeat the same exercise except that we use the growth rates of retail sales along with the growth rate of the other PFEI's. Comparing the results of Table 4 and 5, we find that while retail sales series tends to have a higher correlation than HBA, they tend to lead by less, implying that this series is more coincident with economic activity than HBA.

4.3. Cross-correlation analysis using retail and manufacturing HBA

One strength of the BFS series is that they are also available by sector. It is natural to wonder about the relationship between the sectoral measures of HBA (i.e., manufacturing HBA and retail HBA) and PFEI's that are associated with these sectors. Table 6 reports the results of the same analysis as in Table 4 except that we use manufacturing HBA instead of the overall HBA. Furthermore, we focus the analysis on the PFEI's that are most closely related to manufacturing (i.e., new orders, shipments of manufacturing, and sales in manufacturing and trade). We find that manufacturing HBA leads these three series by one to two months. For comparison we include the results from Table 4, in which we use the overall HBA. The results show that the correlations tend to be similar. The main difference is that the overall HBA leads the manufacturing PFEI's by significantly more than the manufacturing HBA.

Table 7 reports the results of a similar exercise to the one in Table 4 except that we use the retail HBA and focus on retail sales (we include the results of the overall HBA in the table as reference). In this case, retail HBA leads retail sales by more than the overall HBA. Furthermore, the retail HBA also has a slightly higher correlation.

4.4. Using vector autoregression analysis to study properties of business application series

We now make use of vector autoregression (VAR) analysis to complement the results from the cross-correlations. The cross-correlations measure the ability of the BFS series to predict changes in a PFEI (e.g., how well can changes in HBA predict changes in nonfarm employment?). The VAR analysis enables providing guidance about the magnitudes of the relationship, e.g. how large of a change in nonfarm employment is associated with a change in HBA.

We use a standard VAR specification:

$$Y_t = A(L)Y_t + \varepsilon_t \ , \tag{1}$$

where Y_t is a vector of observable variables, $A(L)$ is the matrix of VAR coefficients from this autoregressive representation (AR), L is the lag operator and ε_t is a vector of reduced form innovations. We focus our attention on bivariate VAR specifications with, for example, the growth rate of HBA as one variable and the growth rate of one of the other PFEIs as the other variable. Insights from the VAR emerge from inverting the autoregressive (AR) representation in (1) to the moving average (MA) representation given by:

$$Y_t = D(L)\varepsilon_t = B(L)\eta_t \ , \tag{2}$$

where $D(L)$ are the MA coefficients from inverting the AR representation and η_t represents the orthogonalized innovations after making identifying assumptions.[26] Specifically, we use a Cholesky recursive structure for this identification. In a bivariate specification, this amounts to assuming that the orthogonalized innovation is equal to the reduced form innovation for the first variable in the ordering and the orthogonal innovation for the second variable is equal to the component of the reduced form innovation which is orthogonal to the innovation from the first variable. While such assumptions are strong, it is important to remember that the reduced form innovations reflect fluctuations in the variables of interest after controlling for lagged values of all variables in the VAR.

We use the MA representation with the Cholesky identification to estimate the impulse response functions and also to compute forecast error variance decompositions. We focus on a bivariate VAR including monthly year-over-year growth rates in HBA and nonfarm employment. To provide perspective, we also estimate a second bivariate VAR with retail sales and nonfarm employment. We use a lag length of 12 lags for both models. We put HBA first in the Cholesky ordering in the VAR with HBA and nonfarm employment, and retail sales first in the Cholesky ordering in the VAR with both retail sales and nonfarm employment. For both specifications, in unreported results we find that the impulse response functions are robust to a change in the ordering used for the Cholesky identification approach.

Figure 5a shows the orthogonalized impulse response function (IRF) of nonfarm employment growth to a one standard deviation innovation in HBA growth. The growth rate of nonfarm

[26] By definition, the MA coefficients for the current period 0 in terms of the reduced form residuals is the identity matrix, $D(0)=I$. Of greater interest is to specify the MA representation in terms of orthogonalized innovations. This requires identifying assumptions. A common set of identifying assumptions is to use the Cholesky decomposition which imposes short run restrictions on the relationship between the contemporaneous reduced form residuals and the orthogonalized innovations. Let $B(0)=B_0$ and let the relationship be $\eta_t = B_0\varepsilon_t$ and $B(L)=D(L)B_0$. Under Cholesky, B_0 is lower triangular so that identification is through assuming a recursive structure. In a two variable VAR under Cholesky, all of the covariance between the reduced form residuals is attributed to the orthogonalized innovation for the variable specified first in the VAR. Other short run restrictions can be specified with alternative specifications of B_0 motivated by economic theory (such specifications are denoted structural VARs). See Stock and Watson (2001) and references therein for further discussion. While the causal ordering of the variables in a recursive specification can matter significantly, the results of the bivariate VAR specifications considered here are robust to the recursive ordering.

employment increases for approximately 20 months and then the returns to zero. Furthermore, the growth rate peaks around 0.40, which is quantitatively significant. Figure 5(b) shows the same results for a one standard deviation shock to retail sales. We find a similar pattern as with the HBA shock in which there is a positive growth in nonfarm employment that eventually declines to zero. The main difference is that, after a shock to retail sales, the growth rate peaks earlier than when there is a shock to HBA. These results are consistent with HBA leading nonfarm employment by more than retail sales.

We use the associated forecast error variance decomposition (FEVD) to measure the fraction of variance of growth in nonfarm employment accounted for by growth in HBA and retail sales. These results, reported in Table 8, show that HBA accounts for a substantial amount of variation after 12 months (and relatively little after only one or four months). Retail sales, on the other hand, accounts for a substantial amount of variation after four months. In interpreting these findings, most of the variation in nonfarm employment growth is not accounted for by HBA even at 12 months while retail sales accounts for less than 60 percent of nonfarm employment growth at 12 months. Economic conditions that work through other channels are, not surprisingly, substantial contributors to nonfarm employment growth.

In principle, causality may run in both directions. Figure 6a shows impulse response function of HBA growth to an innovation in nonfarm employment growth and we see that the responses are small and not statistically significant. This result along with Figure 5a suggests that HBA growth shock tends to affect nonfarm employment growth rather than the reverse. Figure 6(b) shows the analogous impulse response of retail sales growth to an innovation in nonfarm employment growth. There is a relatively modest positive response in growth rate of retail sales to an innovation in nonfarm employment growth, but the standard errors are large. Comparing Figures 5b and 6b suggests that the response of nonfarm employment to retail sales is more quantitatively important than the reverse.

Appropriate caution is needed in interpreting these simple bivariate VAR results. In a bivariate VAR, there are only two potential sources of variation. In such small-scale VARs, these sources should be interpreted as composite effects. For example, for the VAR with HBA and nonfarm employment, the innovations to HBA should be interpreted as any change in economic conditions that influence the decision to make a high propensity application. Since it takes time to get an employer business up and running, HBA applications are inherently forward looking. In this respect, both current and expected future changes in economic conditions are likely to be captured.[27]

[27] Recall that the innovations in a given period reflect changes in economic conditions over and above any changes in the past that have already been taken into account given the dynamic VAR specification. The nonfarm employment innovations are any changes in economic conditions that influence nonfarm employment that are not already taken into account given the dynamic VAR specification and also are contemporaneously orthogonal to the HBA innovations. Similar remarks apply to the bivariate VAR with retail sales and nonfarm employment.

It is beyond the scope of this paper to consider large scale VAR specifications that permit disentangling these composite forces. However, as a step in that direction we consider a 3-variable VAR with retail sales, HBA, and nonfarm employment growth as the variables. Furthermore, we put retail sales first in the causal ordering so that effects for HBA reflect changes in economic conditions influencing HBA after already accounting for variation in retail sales.

Figure 7 reports the results of an impulse response function in which we shock HBA (panel a) and retail sales (panel b) from the 3-variable VAR specification. We see that the results are very similar to those found in Figure 6 which uses two separate bivariate VAR's. Table 8 reports the forecast error variance decomposition (FEVD) or the fraction of variance of nonfarm employment growth accounted for by growth in HBA and retail sales. After 12 months, we find that the fraction of variance accounted for by HBA does not change substantially.

These findings provide reassurance that the bivariate VAR results showing a strong contribution of HBA shock to variation in nonfarm employment growth are not driven by the omission of factors that jointly influence HBA and nonfarm employment growth. Recall that nonfarm employment growth lags most of the other PFEIs and is a coincident indicator for the Conference Board. Thus, any variable that captures general changes in economic conditions that are leading indicators for subsequent changes in nonfarm employment is likely to be important in a bivariate VAR. However, by adding retail sales and putting it first in the Cholesky ordering in a 3-variable VAR, HBA is capturing economic conditions over and above those accounting for variation in retail sales. Retail sales is an inherently critical variable for this sensitivity check since general changes in economic conditions are likely to impact consumption expenditures quickly.

In summary, the evidence in this section suggests that growth in HBA is a strong leading indicator of nonfarm employment growth, and there are large positive effects of an innovation in HBA growth on nonfarm employment growth over a substantial horizon. From the VAR identification approach, these dynamics can be interpreted causally given the assumptions underlying the Cholesky identification. However, these results don't identify the underlying mechanisms. A natural candidate mechanism is based on the findings discussed above. An increase in HBA is a good predictor for future employer startups and the latter are in turn an important source of job creation. However, other mechanisms may be at work as suggested above in the discussion of the interpretation of bivariate VAR results. It may be that HBA reacts quickly to current or expected changes in economic conditions that are harbingers of future changes in nonfarm employment.[28]

[28] Haltiwanger (2021) uses bivariate VAR specifications to explore the dynamic relationship between the growth in HBA and indicators of business and worker turnover from BED and JOLTS. He finds that an innovation in HBA yields an increase in both measures of turnover over the next several quarters. These findings complement those in this paper relating HBA to PFEIs. Moreover, they help make the case that variation in HBA is closely connected to the ongoing process of creative destruction.

4.5. VAR analysis using retail and manufacturing HBA

We estimate two additional bivariate VARs. The first has HBA and manufacturing new orders as endogenous variables. The second has manufacturing HBA and manufacturing new orders as endogenous variables. Figure 8a reports the results of an IRF of manufacturing new orders to a shock in overall HBA. We find that the growth rates increase until approximately 15 months and then subsequently decline to zero. Figure 8(b) reports the results of an IRF of manufacturing new orders to a manufacturing HBA shock. In this case, the growth rate increases until approximately month five and then the effects subside. A comparison of these two figures show that a shock to HBA has a more lasting effect than one on manufacturing HBA. These results are consistent with Table 6 in that manufacturing HBA is more coincident with manufacturing new orders than the overall HBA, which tends to lead by more.

We conduct a similar exercise in which we estimate a bivariate VAR with overall HBA and retail sales as endogenous variables. We also estimate a bivariate VAR with retail HBA and retail sales as endogenous variables. We then consider a shock in overall HBA and the retail HBA in each of these VARs and study the effects on retail sales. The results for the shock to overall HBA, reported in Figure 9a, indicate that the growth rate increases for 15 months and then the effects subside. The results for the shock to retail HBA, reported in Figure 9(b), are very similar to the ones in Figure 9a.

4.6. Subperiod analysis

We now repeat our analysis with the 2020-21 time period included, which contains the COVID-19 pandemic recession. Table 9 reports the results analogous to Table 3. We find that the correlations tend to be weaker across the PFEI's. For example, the correlation of retail sales declines from 0.85 to 0.66 and the correlation for HBA declines from 0.64 to 0.33. Furthermore, the lead times tend to decline as well. For example, retail sales lead nonfarm employment by four months without including 2020-21, but only by 1 month with the inclusion of 2021-21; HBA lead nonfarm employment by 11 months without including 2020-21 versus 9 months with the inclusion of 2020-21. It is also interesting to note that the correlation with BA and NHBA become negative with the inclusion of 2020-21.

Table 10 reports the results analogous to Table 4 where we extend the analysis to include 2020-21. We find that HBA still leads most of the other PFEI's except that there is a decline in the strength of the correlation.

To better understand these results, we plot the growth rates of HBA, retail sales, and nonfarm employment through time. Figure 10 shows the growth rates for the entire period (2004 to 2021). HBA exhibited a very substantial decline in 2020 followed by unprecedented growth.

We next study four distinct subperiods. First, in Figure 11, we plot the growth rates through 2019, which is the data that we use for the previous analysis in Sections 4.1 to 4.6. Second, in

Figure 12, we plot the growth rates from 2010 to 2019, which corresponds to the period starting from the end of the Great Recession and finishing before the COVID-19 pandemic. HBA is significantly more volatile than the other two series and we do not see substantial changes in nonfarm employment except at the very beginning of the period.

The second subperiod is 2020-21, which corresponds to the time period of the pandemic, shown Figure 13. The figure shows that the growth in HBA, nonfarm employment, and retail sales move closely together in the early stages of the downturn with all series exhibiting sharp declines in April. All series become less negative in May. By June, both HBA and retail sales growth rates on a year-over-year basis turn positive and stay positive through January 2021. However, growth in nonfarm employment on a year-over-year basis remains negative.

The final subperiod is 2006 to 2010 which corresponds to the time around the Great Recession. Figure 14 shows in a clear way how HBA and retail sales lead nonfarm employment. Furthermore, HBA began its recovery first, followed by retail sales, and then finally nonfarm employment.

Table 11 shows the standard deviation and autocorrelation of the growth rates for HBA, nonfarm employment, and retail sales for all years and the four subperiods mentioned before. The autocorrelation of HBA falls substantially during the period 2010 to 2019, highlighting that the observed volatility in this tranquil period exhibits little persistence. We also see that nonfarm employment and retail sales growth rate have a much higher autocorrelation throughout. Furthermore, the standard deviation of the growth rate tends to be highest for HBA and lowest for nonfarm employment.

Table 12 has the results from the FEVD and is equivalent to Table 8 except that it includes 2020-21. We do not see substantial changes for HBA in the case of the bivariate VAR at 12 months. However, the results become statistically insignificant in the three variable VAR and the contributions are close to zero. There are no substantial changes in the retail sales FEVD results.

In short, the 2020-21 period exhibits extraordinarily large fluctuations in the application series as well as in key economic indicators like nonfarm employment and retail sales. It is not surprising that inclusion of this period has a non-trivial impact on the cross correlation and dynamic patterns in the data as captured by the VAR analysis. A key limitation of using the 2020-21 period for the analysis in this paper is that new business applications tend to substantially lead fluctuations in other indicators. This suggests that inferences in this period await further data. However, another challenge is that even amongst existing PFEIs the pandemic has led to distinct cross correlation patterns. This is evident in the strong recovery of retail sales compared to employment. It is also noteworthy that the period 2010-2019 was a relatively tranquil period without much systematic variation in the business applications series. The application series does exhibit some inherent high frequency noisiness that is more apparent during such tranquil times. Put differently, as is evident in the pre-Great Recession and Great Recession periods, it is systematic and persistent changes in new business applications that are highly predictive for future movements in key indicators like nonfarm employment.

5. Conclusion

Business applications from the BFS provide timely and high frequency information on early-stage entrepreneurial activity -- a precursor of both employer and non-employer business formations in the future. This paper has examined the properties of three business application series from the BFS in relation to existing monthly PFEIs. The analysis indicates that applications for likely employers (HBA) are particularly useful as early indicators of aggregate economic activity. The HBA series leads most PFEIs and appears to be an especially strong early indicator of total nonfarm employment and has a high leading positive correlation with it in terms of year-over-year monthly growth rates. Compared with the 19 monthly PFEIs analyzed, HBA ranks second in terms of the size of its lead for growth in nonfarm employment and ranks in the bottom half in terms of the absolute value of its correlation with nonfarm employment growth. In retrospect, HBA series would have been a highly useful leading indicator during the Great Recession, if the series were available and its properties were known at that time. Figure 3 indicates that HBA series start to decline substantially in the months leading up to and during the early months of Great Recession, signaling a strong worsening of economic conditions ahead.[29]

Business applications as a whole (BA) is also a leading indicator of total nonfarm employment, but its correlation with nonfarm employment is weaker and its lead is smaller, potentially owing to the fact that it contains a large volume of applications that are not likely to become employer businesses. These applications do not generate employment for others and have little to contribute to the statistics on business activity as captured by PFEIs.

The set of likely non-employer applications (NHBA) is of distinct interest, as it contains information on non-employer business formation and self-employment trends. This series could be especially useful for tracking the rise of self-employment and gig jobs in the U.S. economy – see Abraham et al. (2021) for challenges in measuring the latter. Work is in progress to understand the nature and timing of non-employer business formation from business applications, in comparison to employer business formation (Dinlersoz and Luque (2021)).

Finally, further work is needed to understand the mechanisms underlying the dynamic empirical relationships documented here. Specifically, is the strong leading nature of HBA due to the mechanism that it closely tracks future employer startups and the latter in turn have important implications for economic activity? Alternatively, is this pattern driven by the fact that nascent

[29] One caution to this assessment is that the properties of the HBA series established here themselves heavily depend on the behavior of HBA around the Great Recession. Whether these properties would have been the same without the applications data for the Great Recession is an open question, since the data pertaining to earlier periods (before 2004q3) are not available at the moment – though the earlier data may be available from the IRS in the future.

entrepreneurs are inherently forward-looking so that changes in their behavior is a good indicator for future activity? Both as well as other mechanisms may be at work. Even without having sorted out the driving forces, the analysis presented here suggests HBA is a useful novel leading indicator of economic activity.

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Table 1. Principal Federal Economic Indicators (PFEIs) by frequency and federal agency

Indicator Frequency	Federal Agency	PFEI Data Product
Weekly	Energy Information Administration	• Weekly Natural Gas Storage Report
Monthly	Bureau of the Census	• Value of Construction Put in Place* • New Residential Construction* • New Residential Sales* • Monthly Wholesale Trade* • Advance Monthly Sales for Retail and Food Services* • U.S. International Trade in Goods and Services • Manufacturing and Trade: Inventories and Sales* • Manufacturers' Shipments, Inventories, and Orders* • Advance Report on Durable Goods - Manufacturers' Shipments, Inventories, and Orders*
	Bureau of Labor Statistics	• The Employment Situation* • Producer Price Indexes • Consumer Price Index • Real Earnings* • Employment Cost Index • U.S. Import and Export Price Indexes
	National Agriculture Statistics Service	• Agricultural Prices • Crop Production • Cattle on Feed
	Bureau of Economic Analysis	• Personal Income and Outlays • U.S. International Trade in Goods and Services
	Federal Reserve Board	• Industrial Production and Capacity Utilization* • Consumer Credit
	World Agricultural Outlook Board	• World Agricultural Supply and Demand Estimates
	Foreign Agricultural Service	• World Agricultural Production
Quarterly	Bureau of the Census	• Quarterly Financial Report - Manufacturing, Mining, Wholesale Trade, and Selected Service Industries • Quarterly Financial Report - Retail Trade • Housing Vacancies • Quarterly Services
	Bureau of Labor Statistics	• Productivity and Costs
	National Agriculture Statistics Service	• Grain Stocks • Hogs and Pigs
	Bureau of Economic Analysis	• Corporate Profits • U.S. International Transactions • Gross Domestic Product
Semiannual	National Agriculture Statistics Service	• Plantings

Notes: (*) indicates series analyzed in relation to the BFS series

Table 2. PFEI data series used in the analysis

PFEI	Series used in the analysis
Advance Monthly Sales for Retail and Food Services	U.S. Total Retail Trade and Food Services Monthly Sales (Millions of Dollars)
Construction Spending	U.S. Total Annual Rate for Total Construction (Millions of Dollars)
Manufacturers' Shipments, Inventories, and Orders	U.S. Total Manufacturing Value of Shipments (Millions of Dollars)
	U.S. Total Manufacturing Value of New Orders (Millions of Dollars)
Manufacturing and Trade Inventories and Sales	U.S. Total Business Monthly Sales (Millions of Dollars)
	U.S. Total Business Monthly Inventories (Millions of Dollars)
Monthly Wholesale Trade: Sales and Inventories	U.S. Total Merchant Wholesalers (excluding Manufacturers' Sales Branches and Offices) Monthly Sales (Millions of Dollars)
	U.S. Total Merchant Wholesalers (excluding Manufacturers' Sales Branches and Offices) Monthly Inventories (Millions of Dollars)
New Home Sales	U.S. Annual Rate for New Single-Family House Sold (Thousands of Units)
	U.S. New Single-Family Houses for Sales (Thousands of Units)
New Residential Construction	U.S. Annual Rate for Housing Units Authorized in Permit-Issuing Places (Thousands of Units)
	U.S. Annual Rate for Housing Units Completed (Thousands of Units)
	U.S. Annual Rate for Housing Units Started (Thousands of Units)
Advance Monthly Manufacturers' Shipments, Inventories and Orders	U.S. Total of New Orders for Durable Goods (Millions of Dollars)
The Employment Situation	U.S. Total Nonfarm Employees
	U.S. Total Private Sector Employees
	U.S. Unemployment rate
Real Earnings	Real average hourly earnings of production and nonsupervisory employees
Industrial Production and Capacity Utilization	Industrial Production Index

Notes: All series are seasonally adjusted.

Table 3. Cross-correlations: PFEI growth rate and growth rate in nonfarm employment (all years except 2020-21)

Series name	Timing	Correlation	# of Periods
Advance Monthly Sales Retail and Food Services	Leading	0.848*** (0.040)	-4
Construction Spending	Lagging	0.844*** (0.041)	1
Industrial Production	Leading	0.801*** (0.046)	-4
New Single-family Homes for Sale	Lagging	0.798*** (0.046)	1
Manufacturing and Trade Inventories	Lagging	0.789*** (0.047)	1
New Residential Construction Permits	Leading	0.785*** (0.047)	-8
New Residential Construction Units Started	Leading	0.773*** (0.048)	-7
New Single-family Homes Sold	Leading	0.736*** (0.052)	-12
Durable Goods New Orders	Leading	0.700*** (0.054)	-4
Wholesale Inventories	Lagging	0.684*** (0.056)	2
New Residential Construction Units Completed	Leading	0.680*** (0.056)	-6
Manufacturing and Trade Sales	Leading	0.642*** (0.058)	-3
HBA	Leading	0.641*** (0.059)	-11
Manufacturing Shipments	Leading	0.615*** (0.060)	-3
Manufacturing New Orders	Leading	0.610*** (0.060)	-3
Wholesale Sales	Leading	0.540*** (0.064)	-3
Real Hourly Earnings Production and Nonsupervisory Employees	Leading	-0.463*** (0.068)	-2
BA	Leading	0.445*** (0.068)	-5
NHBA	Leading	0.217** (0.074)	-1

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation.

Table 4. Cross-correlations: HBA growth rate and growth rate of other PFEI's (all years except 2020-21)

Series name	Timing	Correlation	# of Periods
Total Nonfarm Employees	Leading	0.641*** (0.059)	-11
Total Private Sector Employees	Leading	0.635*** (0.059)	-10
Unemployment Rate	Leading	-0.595*** (0.061)	-7
Advance Monthly Sales Retail and Food Services	Leading	0.559*** (0.063)	-6
Manufacturing and Trade Inventories	Leading	0.557*** (0.063)	-11
Industrial Production	Leading	0.531*** (0.065)	-8
New Single-family Homes for Sale	Leading	0.526*** (0.065)	-8
New Single-family Homes Sold	Lagging	0.481*** (0.067)	5
Wholesale Inventories	Leading	0.465*** (0.068)	-12
New Residential Construction Units Started	Coincident	0.464*** (0.068)	0
Construction Spending	Leading	0.464*** (0.068)	-12
Durable Goods New Orders	Leading	0.461*** (0.068)	-8
New Residential Construction Units Completed	Leading	0.454*** (0.068)	-1
New Residential Construction Permits	Lagging	0.453*** (0.068)	3
Manufacturing and Trade Sales	Leading	0.439*** (0.068)	-10
Manufacturing Shipments	Leading	0.434*** (0.069)	-10
Manufacturing New Orders	Leading	0.415*** (0.069)	-8
Wholesale Sales	Leading	0.386*** (0.070)	-9
Real Hourly Earnings Production and Nonsupervisory Employees	Leading	-0.283*** (0.073)	-12

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation.

Table 5. Cross-correlations: Retail sales growth rate and growth rate of other PFEI's (all years except 2020-21)

Series name	Timing	Correlation	# of Periods
Manufacturing and Trade Inventories	Leading	0.906*** (0.032)	-5
Industrial Production	Leading	0.899*** (0.033)	-1
Manufacturing and Trade Sales	Coincident	0.899*** (0.033)	0
Manufacturing Shipments	Leading	0.874*** (0.037)	-1
Manufacturing New Orders	Coincident	0.863*** (0.039)	0
Total Private Sector Employees	Leading	0.862*** (0.039)	-4
Durable Goods New Orders	Leading	0.859*** (0.039)	-1
Unemployment Rate	Leading	-0.855*** (0.039)	-3
Wholesale Inventories	Leading	0.855*** (0.040)	-7
Total Nonfarm Employees	Leading	0.848*** (0.040)	-4
Wholesale Sales	Leading	0.835*** (0.042)	-1
Real Hourly Earnings Production and Nonsupervisory Employees	Leading	-0.723*** (0.053)	-1
New Residential Construction Units Started	Coincident	0.690*** (0.055)	0
New Residential Construction Permits	Lagging	0.684*** (0.056)	1
Construction Spending	Leading	0.585*** (0.062)	-6
New Single-family Homes Sold	Lagging	0.548*** (0.064)	6
New Single-family Homes for Sale	Leading	0.503*** (0.066)	-5
New Residential Construction Units Completed	Leading	0.449*** (0.068)	-2

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation.

Table 6. Cross-correlations: Manufacturing-HBA growth rate and growth rate of PFEI's related to manufacturing

(all years except 2020-21)

Series name	HBA Series	Timing	Correlation	# of Periods
Manufacturing New Orders	Manufacturing	Leading	0.421*** (0.069)	-2
Manufacturing and Trade Sales	Manufacturing	Leading	0.413*** (0.069)	-1
Manufacturing Shipments	Manufacturing	Leading	0.403*** (0.070)	-2
Manufacturing and Trade Sales	National	Leading	0.439*** (0.069)	-10
Manufacturing Shipments	National	Leading	0.434*** (0.069)	-10
Manufacturing New Orders	National	Leading	0.415*** (0.069)	-8

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation within HBA manufacturing and HBA national.

Table 7. Cross-correlations: Retail-HBA growth rate and growth rate of PFEI's related to retail

(all years except 2020-21)

Series name	HBA Series	Timing	Correlation	# of Periods
Advance Monthly Sales Retail and Food Services	Retail	Leading	0.633*** (0.059)	-9
Advance Monthly Sales Retail and Food Services	National	Leading	0.559*** (0.063)	-6

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient).

Table 8. Forecast Error Variance Decomposition (FEVD): Fraction of variance of nonfarm employment accounted for by HBA and retail sales

(all years except 2020-21)

Specification	**Period**	**HBA**	**Advanced Monthly Sales Retail and Food Services**
	1	0.010	0.122*
		(0.016)	(0.048)
Bivariate VAR	4	0.037	0.523***
		(0.039)	(0.084)
	12	0.430**	0.574***
		(0.131)	(0.144)
	1	0.002	0.053
		(0.006)	(0.034)
3 variable VAR	4	0.009	0.428***
		(0.016)	(0.089)
	12	0.360***	0.316**
		(0.122)	(0.122)

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 9. Cross-correlations: PFEI growth rate and growth rate in nonfarm employment (all years)

Series name	Timing	Correlation	# of Periods
Industrial Production	Coincident	0.731*** (0.050)	0
Manufacturing and Trade Inventories	Coincident	0.702*** (0.052)	0
Advance Monthly Sales Retail and Food Services	Leading	0.664*** (0.055)	-1
Real Hourly Earnings Production and Nonsupervisory Employees	Coincident	-0.663*** (0.055)	0
Wholesale Inventories	Coincident	0.610*** (0.058)	0
New Single-family Homes for Sale	Lagging	0.557*** (0.061)	1
Manufacturing and Trade Sales	Leading	0.556*** (0.061)	-1
Manufacturing Shipments	Leading	0.553*** (0.061)	-1
Durable Goods New Orders	Leading	0.553*** (0.061)	-1
Wholesale Sales	Leading	0.536*** (0.062)	-1
Manufacturing New Orders	Leading	0.535*** (0.062)	-1
Construction Spending	Lagging	0.505*** (0.063)	1
New Residential Construction Permits	Leading	0.413*** (0.067)	-5
NHBA	Lagging	-0.405*** (0.067)	3
BA	Lagging	-0.396*** (0.068)	3
New Residential Construction Units Started	Leading	0.390*** (0.068)	-7
New Residential Construction Units Completed	Leading	0.387*** (0.068)	-2
New Single-family Homes Sold	Leading	0.330*** (0.069)	-12
HBA	Leading	0.326*** (0.070)	-9

Notes: * p<0.05, ** p<0.01, *** p<0.001. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation.

Table 10. Cross-correlations of HBA growth and growth of other PFEI's (all years)

Series name	Timing	Correlation	# of Periods
New Single-family Homes Sold	Coincident	0.474*** (0.065)	0
Advance Monthly Sales Retail and Food Services	Coincident	0.432*** (0.066)	0
New Residential Construction Units Started	Coincident	0.425*** (0.067)	0
New Single-family Homes for Sale	Leading	0.405*** (0.067)	-7
Manufacturing and Trade Inventories	Leading	0.397*** (0.067)	-12
New Residential Construction Units Completed	Leading	0.388*** (0.068)	-1
New Residential Construction Permits	Coincident	0.384*** (0.068)	0
Industrial Production	Leading	0.353*** (0.069)	-8
Construction Spending	Leading	0.351*** (0.069)	-12
Total Private Sector Employees	Leading	0.337*** (0.069)	-9
Durable Goods New Orders	Leading	0.330*** (0.069)	-5
Total Nonfarm Employees	Leading	0.326*** (0.070)	-9
Manufacturing and Trade Sales	Leading	0.325*** (0.070)	-10
Wholesale Inventories	Leading	0.321*** (0.070)	-12
Manufacturing Shipments	Leading	0.319*** (0.070)	-10
Manufacturing New Orders	Leading	0.307*** (0.070)	-9
Unemployment Rate	Lagging	0.296*** (0.070)	3
Real Hourly Earnings Production and Nonsupervisory Employees	Lagging	0.282*** (0.071)	3
Wholesale Sales	Leading	0.279*** (0.071)	-9

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in parenthesis (calculated using the formula for the standard error of Pearson's correlation coefficient). Table is sorted by the absolute value of the correlation.

Table 11. Standard deviation and autocorrelation of growth rates for HBA, nonfarm employment, and retail sales

	HBA		Nonfarm employment		Retail and food services sales	
Years	Standard deviation	Auto correlation	Standard deviation	Auto correlation	Standard deviation	Auto correlation
All	10.94	0.50	2.72	0.89	4.43	0.86
All except 2020-21	8.18	0.40	1.72	0.99	4.05	0.94
2010-19	5.83	-0.11	0.86	0.86	1.60	0.80
2020-21	25.84	0.53	4.83	0.47	8.00	0.47
2006-10	9.23	0.69	2.31	0.98	5.99	0.93

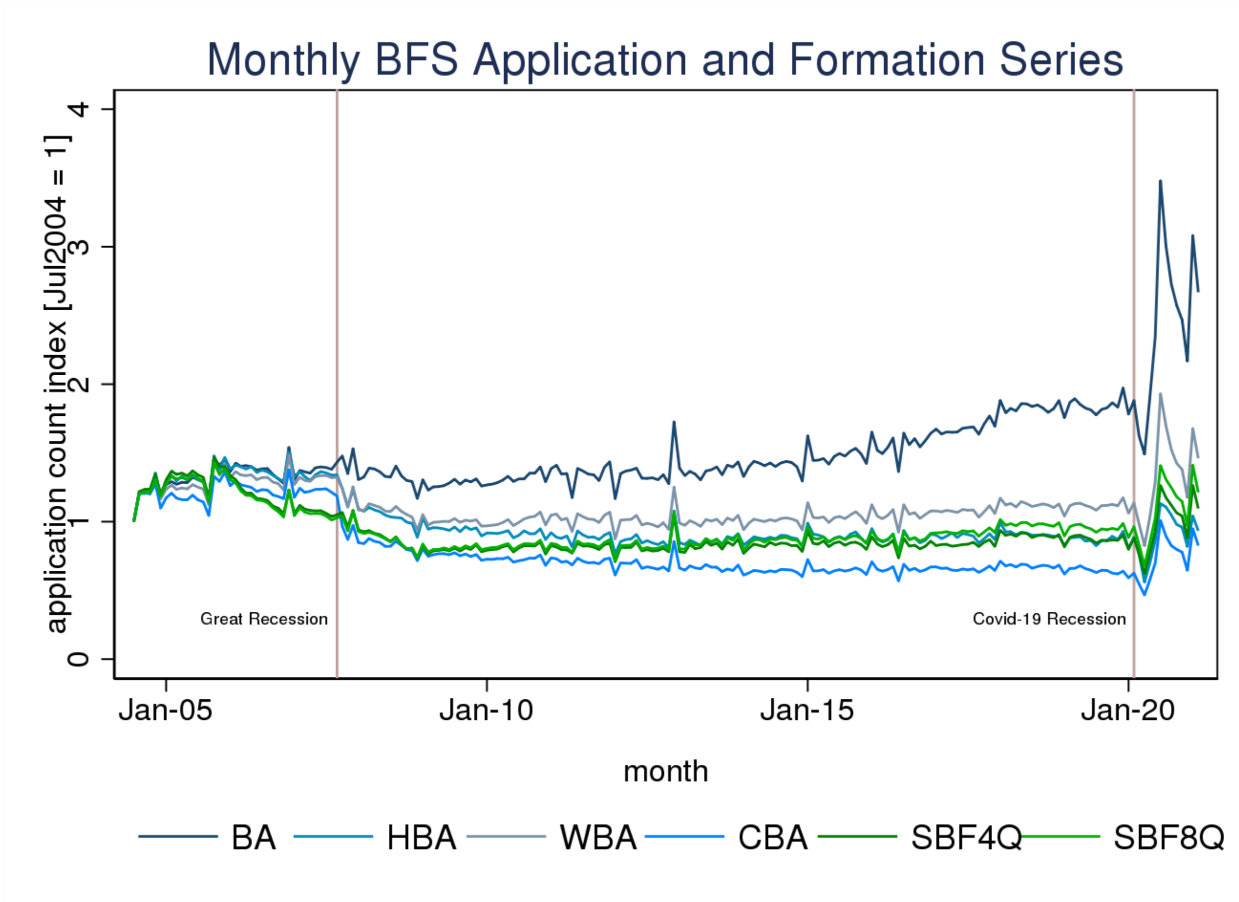
Table 12. Forecast Error Variance Decomposition (FEVD): Fraction of variance of nonfarm employment accounted for by HBA and retail sales

(all years)

Specification	Period	HBA	Advanced Monthly Sales Retail and Food Services
Bivariate VAR	1	0.137**	0.480***
		(0.048)	(0.055)
	4	0.213**	0.842***
		(0.078)	(0.032)
	12	0.268*	0.832***
		(0.126)	(0.126)
3 variable VAR	1	0.015	0.526***
		(0.013)	(0.052)
	4	0.008	0.858***
		(0.008)	(0.029)
	12	0.037	0.806***
		(0.040)	(0.109)

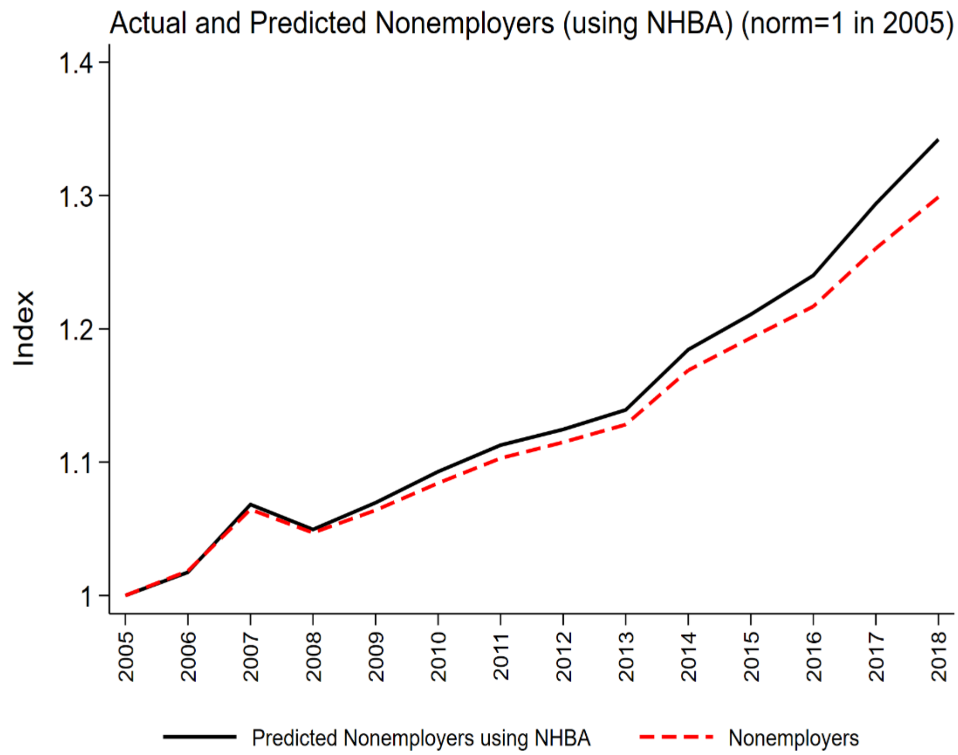
Notes: * p<0.05, ** p<0.01, *** p<0.001.

Figure 1. Monthly business application and formation series from the BFS



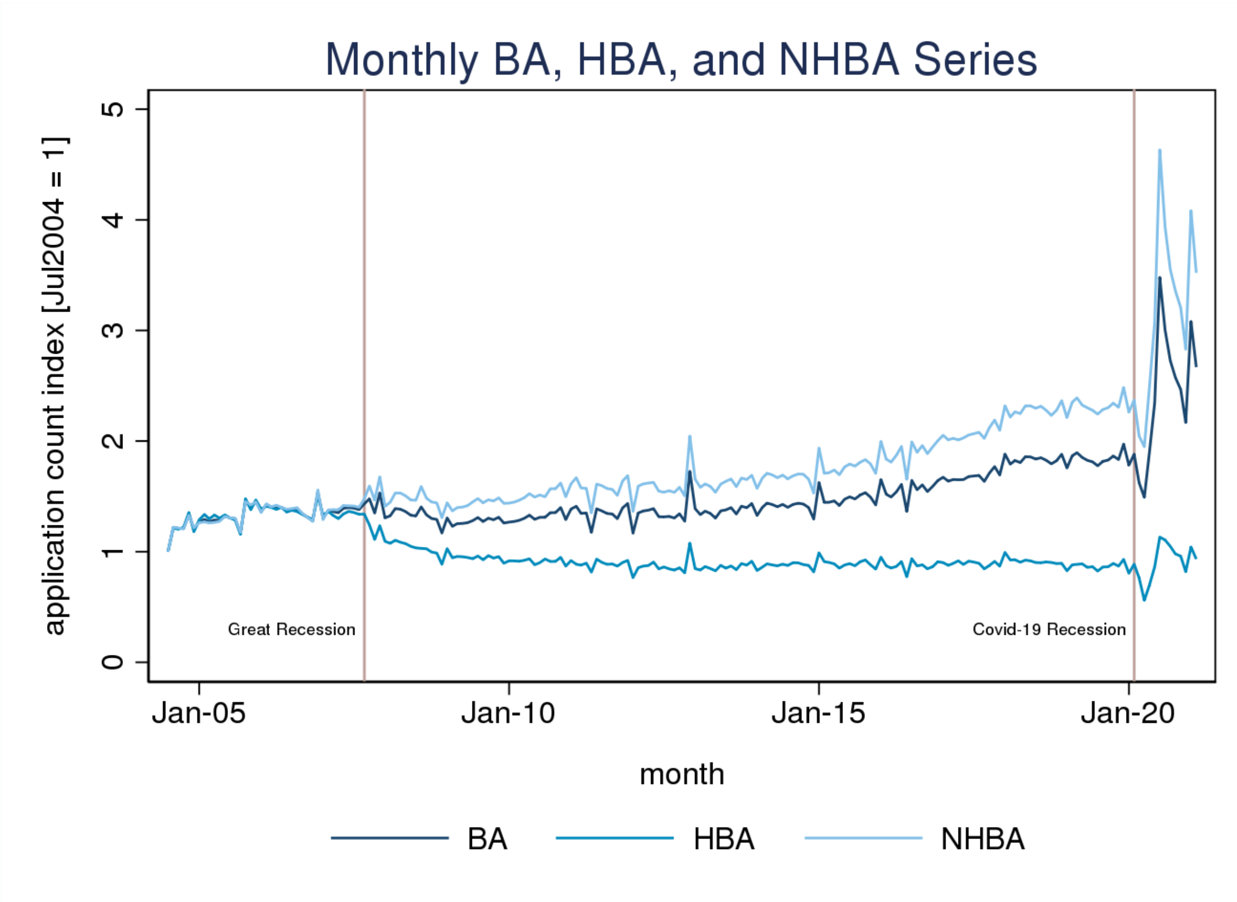
Notes: All series seasonally adjusted

Figure 2. NES series and projected NES using NHBA



Notes: BFS and NES statistics from Census. Predicted non-employers using NHBA uses exit rates from non-employers from Davis et. al. (2009) and entry rates based on NHBA. See Haltiwanger (2021) for further discussion.

Figure 3. Monthly BFS business application series used in the analysis

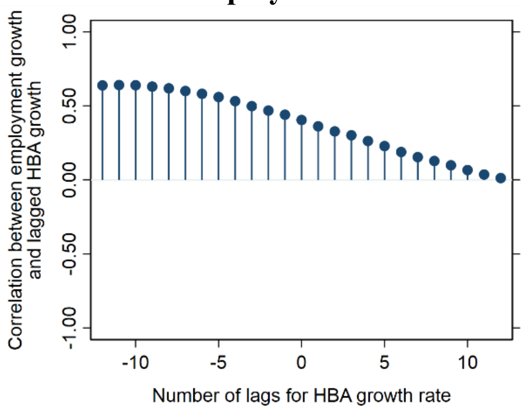


Notes: All series seasonally adjusted

Figure 4. Cross-correlograms

(all years except 2020)

(a) Cross-correlogram of nonfarm employment and HBA



(b) Cross-correlogram of nonfarm employment and retail sales

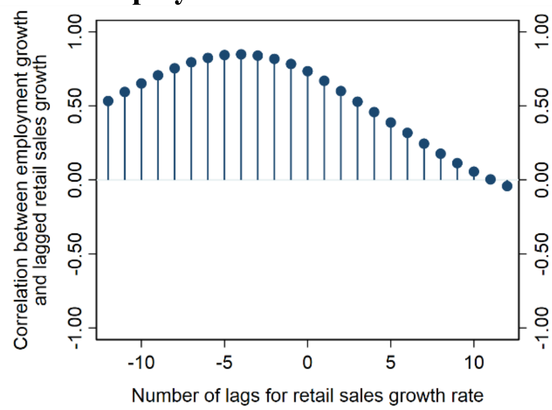
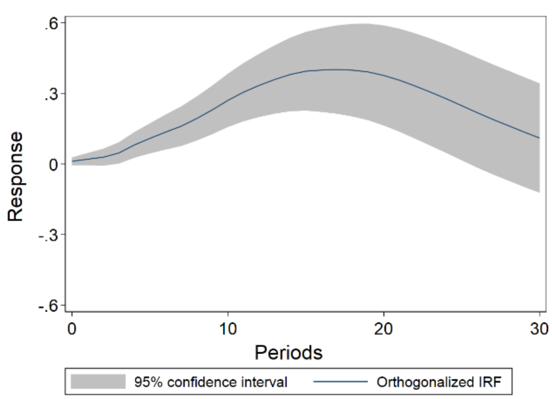


Figure 5. Impulse response functions of nonfarm employment

(all years except 2020)

(a) Impulse response function of nonfarm employment to HBA shock



(b) Impulse response function of nonfarm employment to retail sales shock

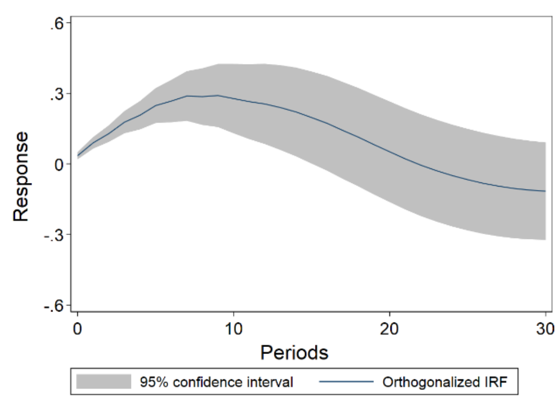
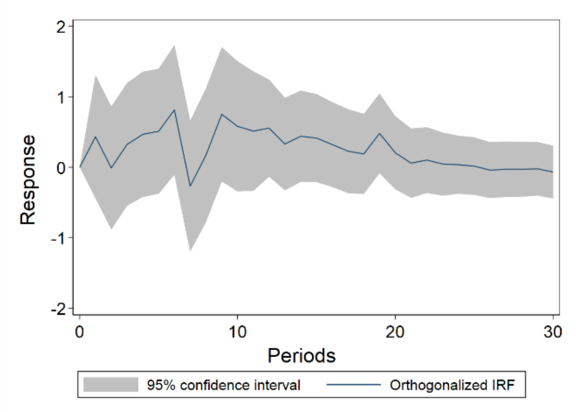


Figure 6. Impulse response function of a nonfarm employment shock

(all years except 2020)

(a) Impulse response function of HBA to nonfarm employment shock



(b) Impulse response function of retail sales to nonfarm employment shock

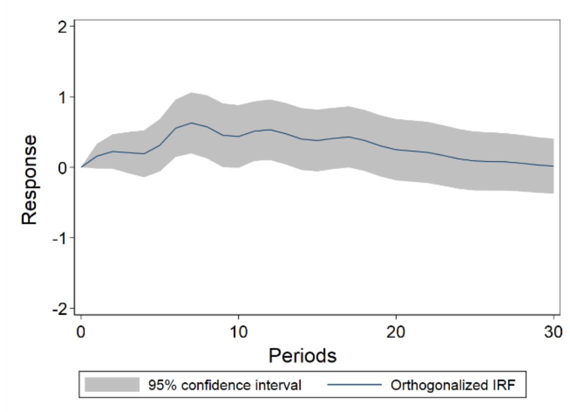
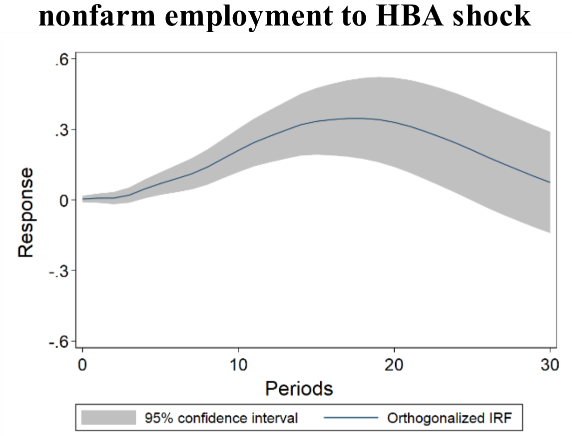


Figure 7. Impulse response functions of nonfarm employment, three-variable VAR

(all years except 2020)

(a) Impulse response function of nonfarm employment to HBA shock



(b) Impulse response function of nonfarm employment to retail sales shock

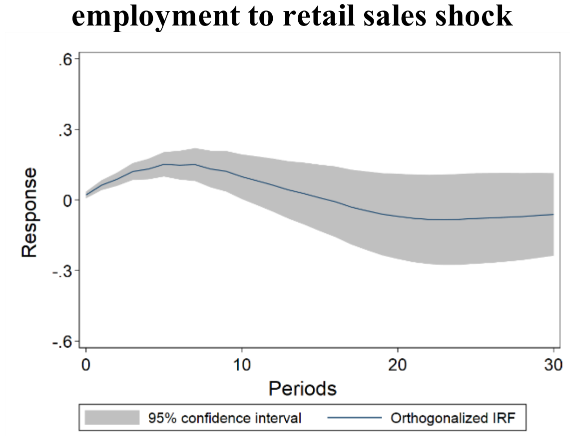
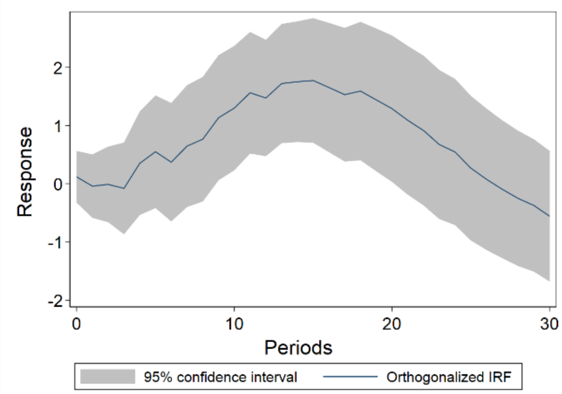


Figure 8. Impulse response function of HBA shock and manufacturing HBA shock (all years except 2020)

(a) Impulse response function of manufacturing new orders to HBA shock



(b) Impulse response function of manufacturing new orders to manufacturing HBA shock

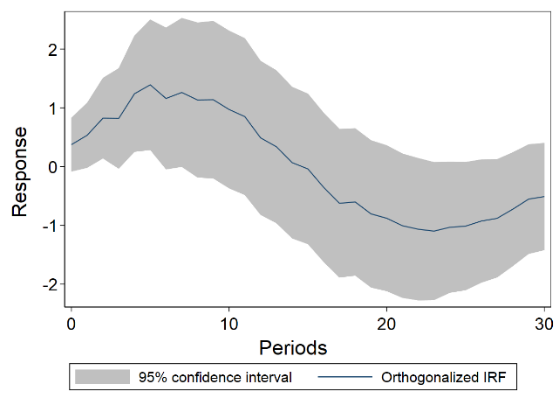
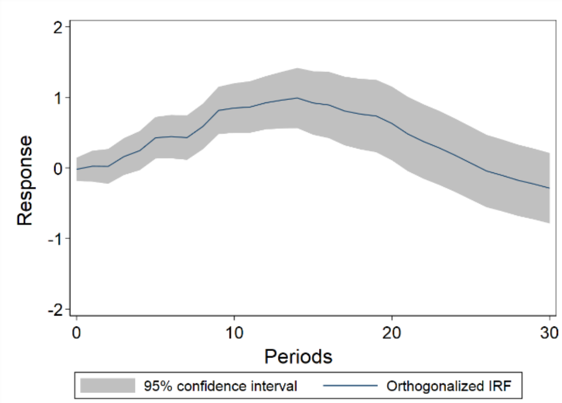


Figure 9. Impulse response function of HBA shock and retail HBA shock (all years except 2020)

(a) Impulse response function of retail sales to HBA shock



(b) Impulse response function of retail sales to HBA retail shock

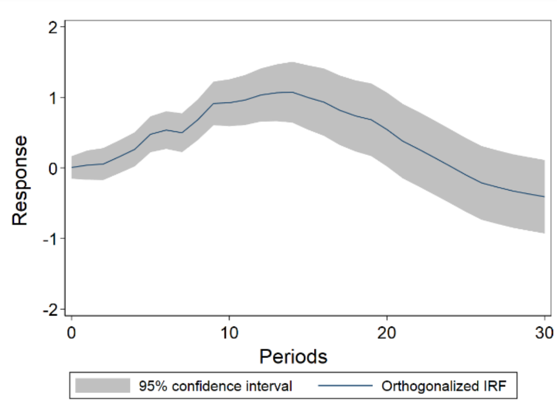


Figure 10. Growth rate of HBA, retail sales, and nonfarm employees (all years)

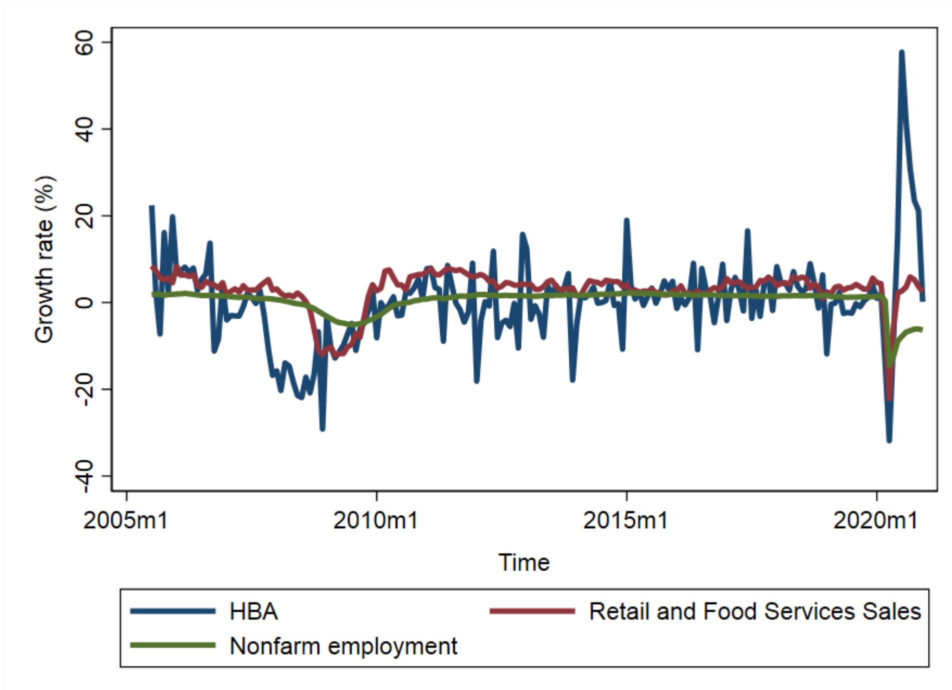


Figure 11. Growth rate of HBA, retail sales, and nonfarm employees (all years up to 2019)

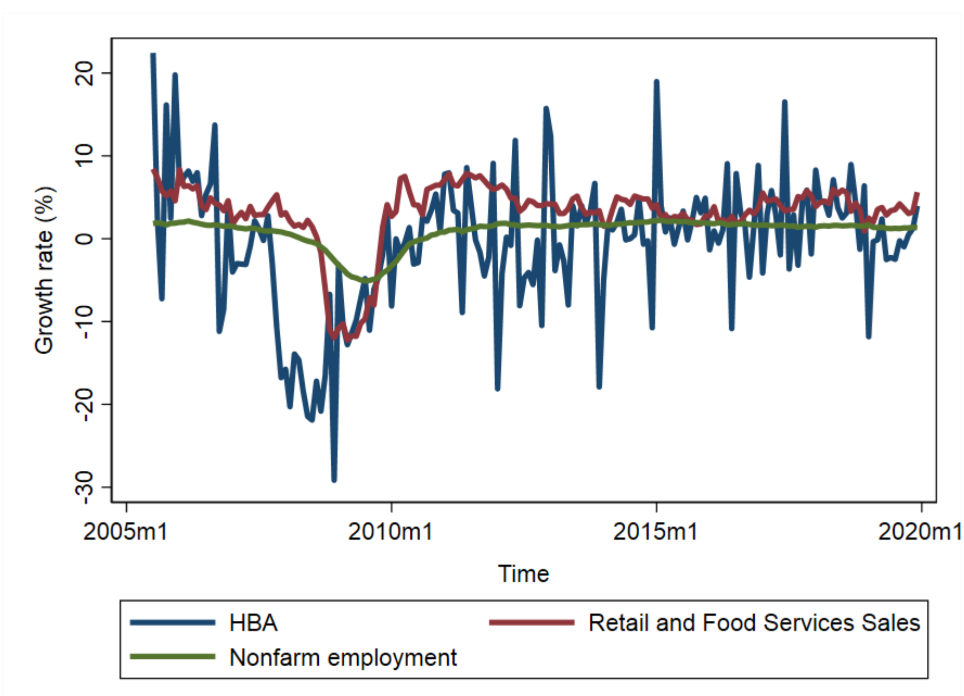


Figure 12. Growth rate of HBA, retail sales, and nonfarm employees (2010-2019)

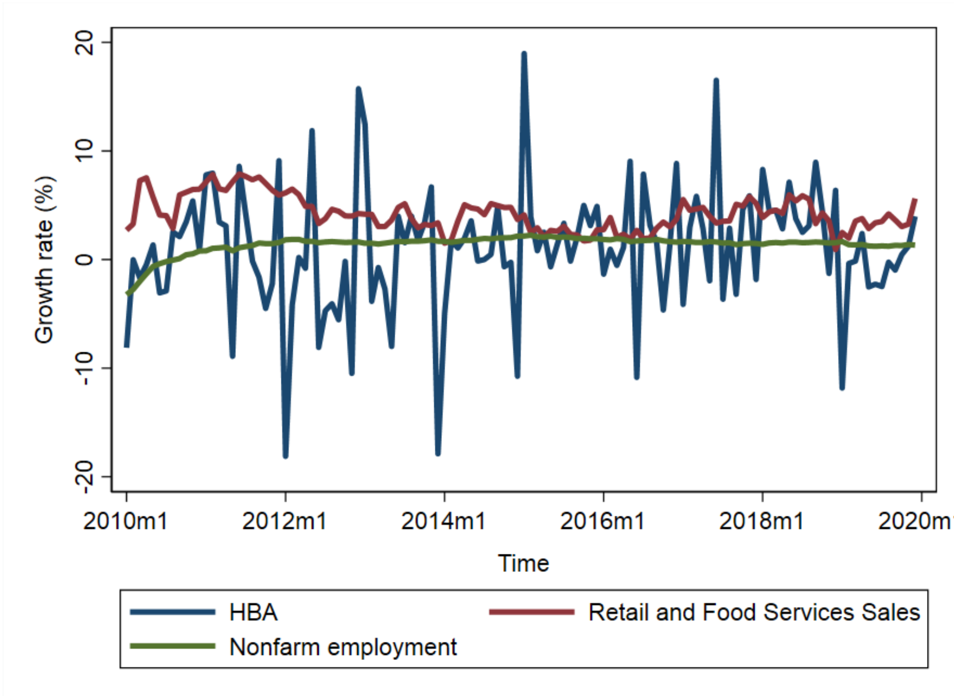


Figure 13. Growth rate of HBA, retail sales, and nonfarm employees (2020-21)

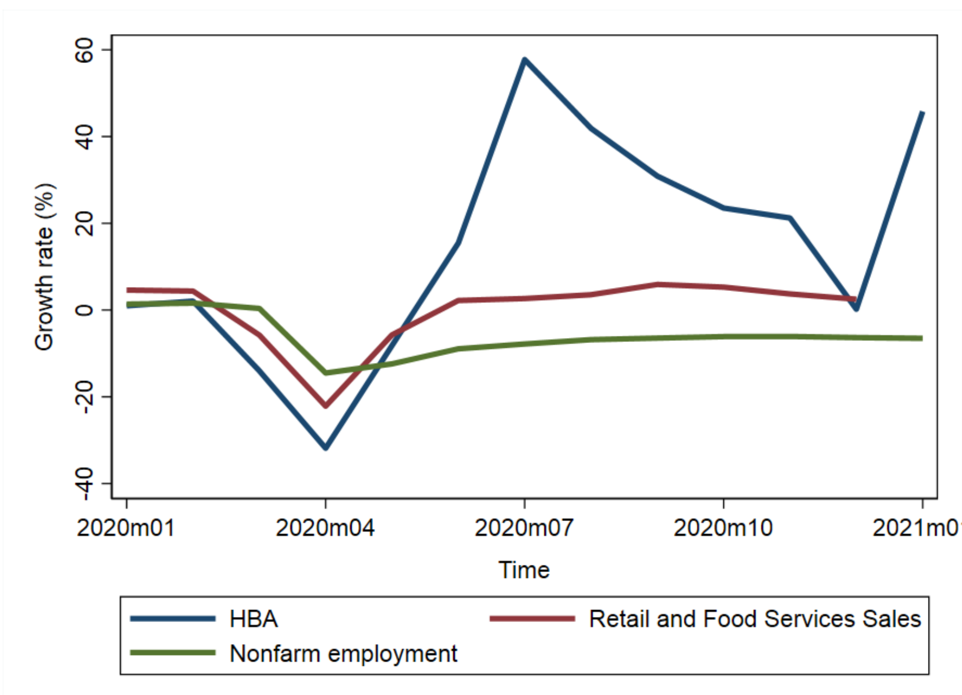


Figure 14. Growth rate of HBA, retail sales, and nonfarm employees (2006-10)